Convolutional neural network

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In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery.

CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing.[1] They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.[2][3]

Convolutional networks were inspired by biological processes[4][5][6][7] in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

They have applications in image and video recognition, recommender systems,[8] image classification, medical image analysis, and natural language processing.[9]

Design

A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, RELU layer i.e. activation function, pooling layers, fully connected layers and normalization layers.[10]

Description of the process as a convolution in neural networks is by convention. Mathematically it is a cross-correlation rather than a convolution (although cross-correlation is a related operation). This only has significance for the indices in the matrix, and thus which weights are placed at which index.

Convolutional

Convolutional layers apply a convolution operation to the input, passing the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli.[11]

Each convolutional neuron processes data only for its receptive field. Although fully connected feedforward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in a shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10000 weights for each neuron in the second layer. The convolution operation brings a solution to this problem as it reduces the number of free parameters, allowing the network to be deeper with fewer parameters.[12] For instance, regardless of image size, tiling regions of size 5 x 5, each with the same shared weights, requires only 25 learnable parameters. In this way, it resolves the vanishing or exploding gradients problem in training traditional multi-layer neural networks with many layers by using backpropagation.

Pooling

Convolutional networks may include local or global pooling layers,[clarification needed] which combine the outputs of neuron clusters at one layer into a single neuron in the next layer.[13][14] For example, max pooling uses the maximum value from each of a cluster of neurons at the prior layer.[15] Another example is average pooling, which uses the average value from each of a cluster of neurons at the prior layer.[16]

Fully connected

Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multi-layer perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images.

Receptive field

In neural networks, each neuron receives input from some number of locations in the previous layer. In a fully connected layer, each neuron receives input from every element of the previous layer. In a convolutional layer, neurons receive input from only a restricted subarea of the previous layer. Typically the subarea is of a square shape (e.g., size 5 by 5). The input area of a neuron is called its receptive field. So, in a fully connected layer, the receptive field is the entire previous layer. In a convolutional layer, the receptive area is smaller than the entire previous layer.

Weights

Each neuron in a neural network computes an output value by applying some function to the input values coming from the receptive field in the previous layer. The function that is applied to the input values is specified by a vector of weights and a bias (typically real numbers). Learning in a neural network progresses by making incremental adjustments to the biases and weights. The vector of weights and the bias are called a filter and represents some feature of the input (e.g., a particular shape). A distinguishing feature of CNNs is that many neurons share the same filter. This reduces memory footprint because a single bias and a single vector of weights is used across all receptive fields sharing that filter, rather than each receptive field having its own bias and vector of weights.[1]

History

CNN design follows vision processing in living organisms.[citation needed]

Receptive fields in the visual cortext

Work by Hubel and Wiesel in the 1950s and 1960s showed that cat and monkey visual cortexes contain neurons that individually respond to small regions of the visual field. Provided the eyes are not moving, the region of visual space within which visual stimuli affect the firing of a single neuron is known as its receptive field.[citation needed] Neighboring cells have similar and overlapping receptive fields.[citation needed] Receptive field size and location varies systematically across the cortex to form a complete map of visual space.[citation needed] The cortex in each hemisphere represents the contralateral visual field.[citation needed]

Their 1968 paper identified two basic visual cell types in the brain:[5]

- simple cells, whose output is maximized by straight edges having particular orientations within their receptive field
- complex cells, which have larger receptive fields, whose output is insensitive to the exact position of the edges in the field.

Hubel and Wiesel also proposed a cascading model of these two types of cells for use in pattern recognition tasks.[17][18]

Neocognitron, origin of the CNN architecture

The "neocognitron"[4] was introduced by Kunihiko Fukushima in 1980.[6][15][19] It was inspired by the above-mentioned work of Hubel and Wiesel. The neocognitron introduced the two basic types of layers in CNNs: convolutional layers, and downsampling layers. A convolutional layer contains units whose receptive fields cover a patch of the previous layer. The weight vector (the set of adaptive parameters) of such a unit is often called a filter. Units can share filters. Downsampling layers contain units whose receptive fields cover patches of previous convolutional layers. Such a unit typically computes the average of the activations of the units in its patch. This downsampling helps to correctly classify objects in visual scenes even when the objects are shifted.

In a variant of the neocognitron called the cresceptron, instead of using Fukushima's spatial averaging, J. Weng et al. introduced a method called max-pooling where a downsampling unit computes the maximum of the activations of the units in its patch.[20] Max-pooling is often used in modern CNNs.[21]

Several supervised and unsupervised learning algorithms have been proposed over the decades to train the weights of a neocognitron.[4] Today, however, the CNN architecture is usually trained through backpropagation.

The neocognitron does not require units located at multiple network positions to have the same trainable weights. This idea appears in 1986 in the book version of a paper on experiments with the backpropagation algorithm.[22]:Figure 14 Neocognitrons were developed in 1988 for temporal signals.[clarification needed][23] Their design was improved in 1998,[24] generalized in 2003[25] and simplified in the same year.[26]

Time delay neural networks

The time delay neural network (TDNN) was introduced in 1987 by Alex Waibel et al. and was the first convolutional network, as it achieved shift invariance.[27] It did so by utilizing weight sharing in combination with back propagation training.[28] Thus, while also using a pyramidal structure as in the neocognitron, it performed a global optimization of the weights, instead of a local one.[27]

TDNNs are convolutional networks that share weights along the temporal dimension.[29] They allow speech signals to be processed time-invariantly. This inspired translation invariance in image processing with CNNs. [28] The tiling of neuron outputs can cover timed stages.[30]

TDNNs now achieve the best performance in far distance speech recognition.[31]

Image recognition with CNNs trained by gradient descent

A system to recognize hand-written ZIP Code numbers[32] involved convolutions in which the kernel coefficients had been laboriously hand designed.[33]

Yann LeCun et al. (1989)[33] used back-propagation to learn the convolution kernel coefficients directly from images of hand-written numbers. Learning was thus fully automatic, performed better than manual coefficient design, and was suited to a broader range of image recognition problems and image types. This approach became a foundation of modern computer vision.

LeNet-5

LeNet-5, a pioneering 7-level convolutional network by LeCun et al. in 1998,[24] that classifies digits, was applied by several banks to recognize hand-written numbers on checks (British English: cheques) digitized in 32x32 pixel images. The ability to process higher resolution images requires larger and more layers of convolutional neural networks, so this technique is constrained by the availability of computing resources.

Shift-invariant neural network

Similarly, a shift invariant neural network was proposed by W. Zhang et al. for image character recognition in 1988.[2][3] The architecture and training algorithm were modified in 1991[34] and applied for medical image processing[35] and automatic detection of breast cancer in mammograms.[36]

A different convolution-based design was proposed in 1988[37] for application to decomposition of one-dimensional electromyography convolved signals via de-convolution. This design was modified in 1989 to other de-convolution-based designs.[38][39]

Neural abstraction pyramid

The feed-forward architecture of convolutional neural networks was extended in the neural abstraction pyramid[40] by lateral and feedback connections.[further explanation needed] The resulting recurrent convolutional network allows for the flexible incorporation of contextual information to iteratively resolve local ambiguities. In contrast to previous models, image-like outputs at the highest resolution were generated.

GPU implementations

Although CNNs were invented in the 1980s, their breakthrough in the 2000s required fast implementations on Graphics Processing Units or GPUs.

In 2004, it was shown by K. S. Oh and K. Jung that standard neural networks can be greatly accelerated on GPUs. Their implementation was 20 times faster than an equivalent implementation on CPU.[41][21] In 2005, another paper also emphasised the value of GPGPU for machine learning.[42]

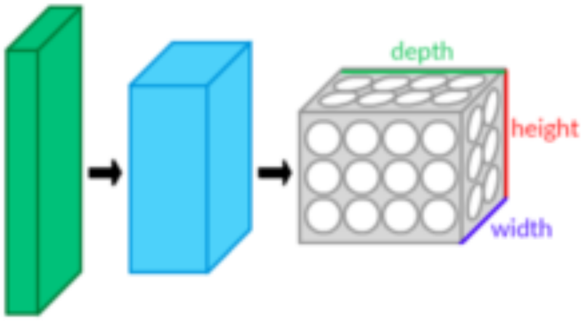
The first GPU-implementation of a CNN was described in 2006 by K. Chellapilla et al. Their implementation was 4 times faster than an equivalent implementation on CPU.[43] Subsequent work also used GPUs, initially for other types of neural networks (different from CNNs), especially unsupervised neural networks.[44][45][46][47]

In 2010, Dan Ciresan et al. at IDSIA showed that even deep standard neural networks with many layers can be quickly trained on GPU by supervised learning through the old method known as backpropagation. Their network outperformed previous machine learning methods on the MNIST handwritten digits benchmark.[48] In 2011, they extended this GPU approach to CNNs, achieving an acceleration factor of 60, with impressive results.[13] In 2011, they used such CNNs on GPU to win an image recognition contest where they achieved superhuman performance for the first time.[49] Between May 15, 2011 and September 30, 2012, their CNNs won no less than four image competitions.[50][21] In 2012, they also significantly improved on the best performance in the literature for multiple image databases, including the MNIST database, the NORB database, the HWDB1.0 dataset (Chinese characters) and the CIFAR10 dataset (dataset of 60000 32x32 labeled RGB images)[15].

Subsequently, a similar GPU-based CNN by Alex Krizhevsky et al. won the ImageNet Large Scale Visual Recognition Challenge 2012.[51] A very deep CNN with over 100 layers by Microsoft won the ImageNet 2015 contest.[52]

Distinguishing features

Traditional multilayer perceptron (MLP) models were successfully used for image recognition.[example needed] However, due to the full connectivity between nodes they suffer from the curse of dimensionality, and thus do not scale well to higher resolution images. A 1000×1000-pixel image with RGB color channels has 3 million dimensions, which is too high to feasibly process efficiently at scale with full connectivity.



CNN layers arranged in 3 dimensions

For example, in CIFAR-10, images are only of size 32×32×3 (32 wide, 32 high, 3 color channels), so a single fully connected neuron in a first hidden layer of a regular neural network would have 32*32*3 = 3,072 weights. A 200×200 image, however, would lead to neurons that have 200*200*3 = 120,000 weights.

Also, such network architecture does not take into account the spatial structure of data, treating input pixels which are far apart in the same way as pixels that are close together. This ignores locality of reference in image data, both computationally and semantically. Thus, full connectivity of neurons is wasteful for purposes such as image recognition that are dominated by spatially local input patterns.

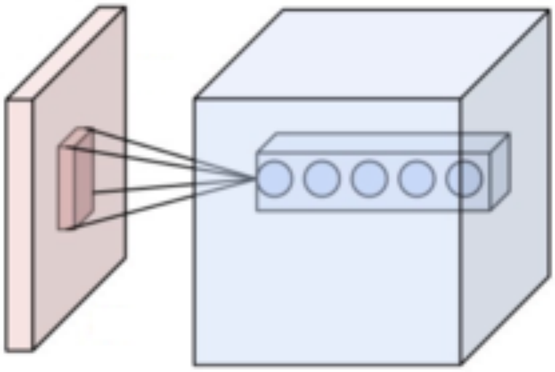
Convolutional neural networks are biologically inspired variants of multilayer perceptrons that are designed to emulate the behavior of a visual cortex. These models mitigate the challenges posed by the MLP architecture by exploiting the strong spatially local correlation present in natural images. As opposed to MLPs, CNNs have the following distinguishing features:

- 3D volumes of neurons. The layers of a CNN have neurons arranged in 3 dimensions: width, height and depth. The neurons inside a layer are connected to only a small region of the layer before it, called a receptive field. Distinct types of layers, both locally and completely connected, are stacked to form a CNN architecture.
- Local connectivity: following the concept of receptive fields, CNNs exploit spatial locality by enforcing a local connectivity pattern between neurons of adjacent layers. The architecture thus ensures that the learned "filters" produce the strongest response to a spatially local input pattern. Stacking many such layers leads to non-linear filters that become increasingly global (i.e. responsive to a larger region of pixel space) so that the network first creates representations of small parts of the input, then from them assembles representations of larger areas.
- Shared weights: In CNNs, each filter is replicated across the entire visual field. These replicated units share the same parameterization (weight vector and bias) and form a feature map. This means that all the neurons in a given convolutional layer respond to the same feature within their specific response field. Replicating units in this way allows for features to be detected regardless of their position in the visual field, thus constituting a property of translation invariance.

Together, these properties allow CNNs to achieve better generalization on vision problems. Weight sharing dramatically reduces the number of free parameters learned, thus lowering the memory requirements for running the network and allowing the training of larger, more powerful networks.

Building blocks

A CNN architecture is formed by a stack of distinct layers that transform the input volume into an output volume (e.g. holding the class scores) through a differentiable function. A few distinct types of layers are commonly used. These are further discussed below.



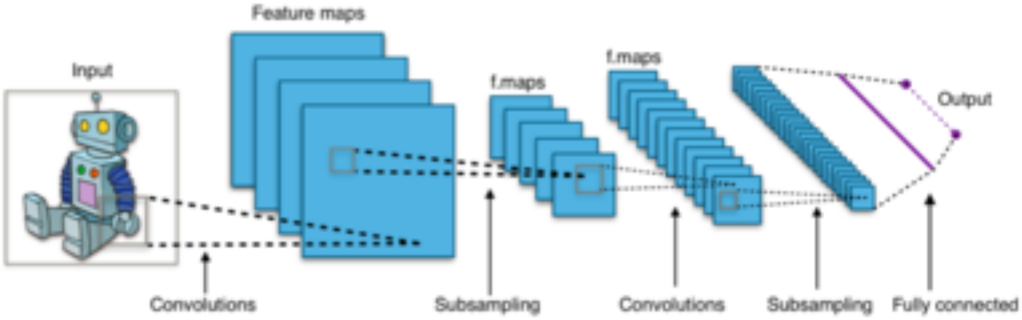
Neurons of a convolutional layer (blue), connected to their receptive field (red)

Convolutional layer

The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input and producing a 2-dimensional activation map of that filter. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input.[nb 1]

Stacking the activation maps for all filters along the depth dimension forms the full output volume of the convolution layer. Every entry in the output volume can thus also be interpreted as an output of a neuron that looks at a small region in the input and shares parameters with neurons in the same activation map.

Local connectivity



Typical CNN architecture

When dealing with high-dimensional inputs such as images, it is impractical to connect neurons to all neurons in the previous volume because such a network architecture does not take the spatial structure of the data into account. Convolutional networks exploit spatially local correlation by enforcing a sparse local connectivity pattern between neurons of adjacent layers: each neuron is connected to only a small region of the input volume.

The extent of this connectivity is a hyperparameter called the receptive field of the neuron. The connections are local in space (along width and height), but always extend along the entire depth of the input volume. Such an architecture ensures that the learnt filters produce the strongest response to a spatially local input pattern.

Spatial arrangement

Three hyperparameters control the size of the output volume of the convolutional layer: the depth, stride and zero-padding.

- The depth of the output volume controls the number of neurons in a layer that connect to the same region of the input volume. These neurons learn to activate for different features in the input. For example, if the first convolutional layer takes the raw image as input, then different neurons along the depth dimension may activate in the presence of various oriented edges, or blobs of color.
- Stride controls how depth columns around the spatial dimensions (width and height) are allocated. When the stride is 1 then we move the filters one pixel at a time. This leads to heavily overlapping receptive fields between the columns, and also to large output volumes. When the stride is 2 then the filters jump 2 pixels at a time as they slide around. Similarly, for any integer $S > 0$a stride of S causes the filter to be translated by S units at a time per output. In practice, stride lengths of $S \geq 3$ are rare. The receptive fields overlap less and the resulting output volume has smaller spatial dimensions when stride length is increased.[53]
- Sometimes it is convenient to pad the input with zeros on the border of the input volume. The size of this padding is a third hyperparameter. Padding provides control of the output volume spatial size. In particular, sometimes it is desirable to exactly preserve the spatial size of the input volume.
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The spatial size of the output volume can be computed as a function of the input volume size W, the kernel field size of the convolutional layer neurons K, the stride with which they are applied S, and the amount of zero padding P used on the border. The formula for calculating how many neurons "fit" in a given volume is given by

$(W - K + 2P) / S + 1$.

If this number is not an integer, then the strides are incorrect and the neurons cannot be tiled to fit across the input volume in a symmetric way. In general, setting zero padding to be $P = (K - 1) / 2$ when the stride is $S = 1$ ensures that the input volume and output volume will have the same size spatially. However, it's not always completely necessary to use all of the neurons of the previous layer. For example, a neural network designer may decide to use just a portion of padding.

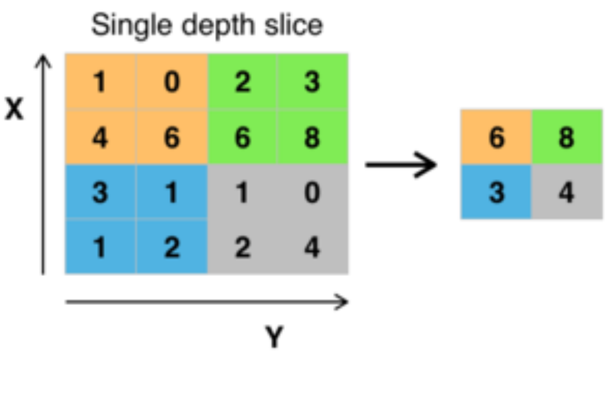
Parameter sharing

A parameter sharing scheme is used in convolutional layers to control the number of free parameters. It relies on one reasonable assumption: if a patch feature is useful to compute at some spatial position, then it should also be useful to compute at other positions. In other words, denoting a single 2-dimensional slice of depth as a depth slice, we constrain the neurons in each depth slice to use the same weights and bias.

Since all neurons in a single depth slice share the same parameters, the forward pass in each depth slice of the convolutional layer can be computed as a convolution of the neuron's weights with the input volume.[nb 2] Therefore, it is common to refer to the sets of weights as a filter (or a kernel), which is convolved with the input. The result of this convolution is an activation map, and the set of activation maps for each different filter are stacked together along the depth dimension to produce the output volume. Parameter sharing contributes to the translation invariance of the CNN architecture.

Sometimes, the parameter sharing assumption may not make sense. This is especially the case when the input images to a CNN have some specific centered structure; for which we expect completely different features to be learned on different spatial locations. One practical example is when the inputs are faces that have been centered in the image: we might expect different eye-specific or hair-specific features to be learned in different parts of the image. In that case it is common to relax the parameter sharing scheme, and instead simply call the layer a "locally connected layer".

Pooling layer



Max pooling with a 2x2 filter and stride = 2

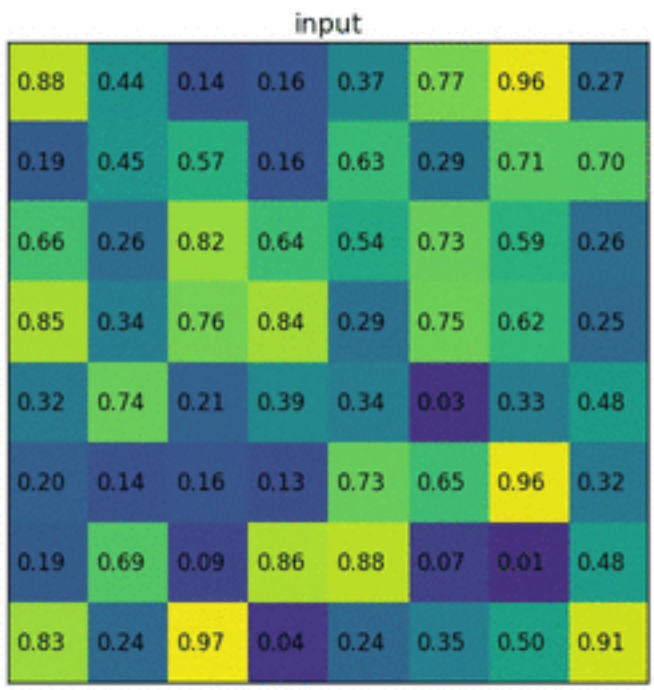
Another important concept of CNNs is pooling, which is a form of non-linear down-sampling. There are several nonlinear functions to implement pooling among which max pooling is the most common. It partitions the input imageinto a set of non-overlapping rectangles and, for each such sub-region, outputs the maximum.

Intuitively, the exact location of a feature is less important than its rough location relative to other features. This is the idea behind the use of pooling in convolutional neural networks. The pooling layer serves to progressively reduce the spatial size of the representation, to reduce the number of parameters, memory footprint and amount of computation in the network, and hence to also control overfitting. It is common to periodically insert a pooling layer between successive convolutional layers in a CNN architecture. The pooling operation provides another form of translation invariance.

The pooling layer operates independently on every depth slice of the input and resizes it spatially. The most common form is a pooling layer with filters of size 2×2 applied with a stride of 2 downsamples at every depth slice in the input by 2 along both width and height, discarding 75% of the activations. In this case, every max operation is over 4 numbers. The depth dimension remains unchanged.

In addition to max pooling, pooling units can use other functions, such as average pooling or ℓ_2-norm pooling. Average pooling was often used historically but has recently fallen out of favor compared to max pooling, which performs better in practice.[54]

Due to the aggressive reduction in the size of the representation,[which?] there is a recent trend towards using smaller filters[55] or discarding pooling layers altogether.[56]



RoI pooling to size 2x2. In this example region proposal (an input parameter) has size 7x5.

"Region of Interest" pooling (also known as RoI pooling) is a variant of max pooling, in which output size is fixed and input rectangle is a parameter.[57]

Pooling is an important component of convolutional neural networks for object detection based on Fast R-CNN[58] architecture.

[Several parts deleted]

Hierarchical coordinate frames

Pooling loses the precise spatial relationships between high-level parts (such as nose and mouth in a face image). These relationships are needed for identity recognition. Overlapping the pools so that each feature occurs in multiple pools, helps retain the information. Translation alone cannot extrapolate the understanding of geometric relationships to a radically new viewpoint, such as a different orientation or scale. On the other hand, people are very good at extrapolating; after seeing a new shape once they can recognize it from a different viewpoint.[69]

Currently, the common way to deal with this problem is to train the network on transformed data in different orientations, scales, lighting, etc. so that the network can cope with these variations. This is computationally intensive for large data-sets. The alternative is to use a hierarchy of coordinate frames and to use a group of neurons to represent a conjunction of the shape of the feature and its pose relative to the retina. The pose relative to retina is the relationship between the coordinate frame of the retina and the intrinsic features' coordinate frame.[70]

Thus, one way of representing something is to embed the coordinate frame within it. Once this is done, large features can be recognized by using the consistency of the poses of their parts (e.g. nose and mouth poses make a consistent prediction of the pose of the whole face). Using this approach ensures that the higher level entity (e.g. face) is present when the lower level (e.g. nose and mouth) agree on its prediction of the pose. The vectors of neuronal activity that represent pose ("pose vectors") allow spatial transformations modeled as linear operations that make it easier for the network to learn the hierarchy of visual entities and generalize across viewpoints. This is similar to the way the human visual system imposes coordinate frames in order to represent shapes.[71]

Applications

Image recognition

CNNs are often used in image recognition systems. In 2012 an error rate of 0.23 percent on the MNIST database was reported.[15] Another paper on using CNN for image classification reported that the learning process was "surprisingly fast"; in the same paper, the best published results as of 2011 were achieved in the MNIST database and the NORB database.[13] Subsequently, a similar CNN called AlexNet[72] won the ImageNet Large Scale Visual Recognition Challenge 2012.

When applied to facial recognition, CNNs achieved a large decrease in error rate.[73] Another paper reported a 97.6 percent recognition rate on "5,600 still images of more than 10 subjects".[7] CNNs were used to assess video quality in an objective way after manual training; the resulting system had a very low root mean square error.[30]

The ImageNet Large Scale Visual Recognition Challenge is a benchmark in object classification and detection, with millions of images and hundreds of object classes. In the ILSVRC 2014,[74] a large-scale visual recognition challenge, almost every highly ranked team used CNN as their basic framework. The winner GoogLeNet[75] (the foundation of DeepDream) increased the mean average precision of object detection to 0.439329, and reduced classification error to 0.06656, the best result to date. Its network applied more than 30 layers. That performance of convolutional neural networks on the ImageNet tests was close to that of humans.[76] The best algorithms still struggle with objects that are small or thin, such as a small ant on a stem of a flower or a person holding a quill in their hand. They also have trouble with images that have been distorted with filters, an increasingly common phenomenon with modern digital cameras. By contrast, those kinds of images rarely trouble humans. Humans, however, tend to have trouble with other issues. For example, they are not good at classifying objects into fine-grained categories such as the particular breed of dog or species of bird, whereas convolutional neural networks handle this.

In 2015 a many-layered CNN demonstrated the ability to spot faces from a wide range of angles, including upside down, even when partially occluded, with competitive performance. The network was trained on a database of 200,000 images that included faces at various angles and orientations and a further 20 million images without faces. They used batches of 128 images over 50,000 iterations.[77]

Video analysis

Compared to image data domains, there is relatively little work on applying CNNs to video classification. Video is more complex than images since it has another (temporal) dimension. However, some extensions of CNNs into the video domain have been explored. One approach is to treat space and time as equivalent dimensions of the input and perform convolutions in both time and space.[78][79] Another way is to fuse the features of two convolutional neural networks, one for the spatial and one for the temporal stream.[80][81][82] Long short-term memory (LSTM) recurrent units are typically incorporated after the CNN to account for inter-frame or inter-clip dependencies.[83][84] Unsupervised learning schemes for training spatio-temporal features have been introduced, based on Convolutional Gated Restricted Boltzmann Machines[85] and Independent Subspace Analysis.[86]

Natural language processing

CNNs have also been explored for natural language processing. CNN models are effective for various NLP problems and achieved excellent results in semantic parsing,[87] search query retrieval,[88] sentence modeling,[89] classification,[90] prediction[91] and other traditional NLP tasks.[92]

Drug discovery

CNNs have been used in drug discovery. Predicting the interaction between molecules and biological proteins can identify potential treatments. In 2015, Atomwise introduced AtomNet, the first deep learning neural network for structure-based rational drug design.[93] The system trains directly on 3-dimensional representations of chemical interactions. Similar to how image recognition networks learn to compose smaller, spatially proximate features into larger, complex structures,[94] AtomNet discovers chemical features, such as aromaticity, sp^3 carbons and hydrogen bonding. Subsequently, AtomNet was used to predict novel candidate biomolecules for multiple disease targets, most notably treatments for the Ebola virus[95] and multiple sclerosis.[96]

Health risk assessment and biomarkers of aging discovery

CNNs can be naturally tailored to analyze a sufficiently large collection of time series data representing one-week-long human physical activity streams augmented by the rich clinical data (including the death register, as provided by, e.g., the NHANES study). A simple CNN was combined with Cox-Gompertz proportional hazards model and used to produce a proof-of-concept example of digital biomarkers of aging in the form of all-causes-mortality predictor.[97]

Checkers game

CNNs have been used in the game of checkers. From 1999 to 2001, Fogel and Chellapilla published papers showing how a convolutional neural network could learn to play checkers using co-evolution. The learning process did not use prior human professional games, but rather focused on a minimal set of information contained in the checkerboard: the location and type of pieces, and the piece differential.[clarify] Ultimately, the program (Blondie24) was tested on 165 games against players and ranked in the highest 0.4%.[98][99] It also earned a win against the program Chinook at its "expert" level of play.[100]

Go

CNNs have been used in computer Go. In December 2014, Clark and Storkey published a paper showing that a CNN trained by supervised learning from a database of human professional games could outperform GNU Go and win some games against Monte Carlo tree search Fuego 1.1 in a fraction of the time it took Fuego to play.[101] Later it was announced that a large 12-layer convolutional neural network had correctly predicted the professional move in 55% of positions, equalling the accuracy of a 6 dan human player. When the trained convolutional network was used directly to play games of Go, without any search, it beat the traditional search program GNU Go in 97% of games, and matched the performance of the Monte Carlo tree search program Fuego simulating ten thousand playouts (about a million positions) per move.[102]

A couple of CNNs for choosing moves to try ("policy network") and evaluating positions ("value network") driving MCTS were used by AlphaGo, the first to beat the best human player at the time.[103]

Fine-tuning

For many applications, little training data is available. Convolutional neural networks usually require a large amount of training data in order to avoid overfitting. A common technique is to train the network on a larger data set from a related domain. Once the network parameters have converged an additional training step is performed using the in-domain data to fine-tune the network weights. This allows convolutional networks to be successfully applied to problems with small training sets.[104]

Human interpretable explanations

End-to-end training and prediction are common practice in computer vision. However, human interpretable explanations are required for critical systems such as a self-driving cars.[105] With recent advances in visual salience, spatial and temporal attention, the most critical spatial regions/temporal instants could be visualized to justify the CNN predictions.[106][107]

Related Architectures

Deep Q-networks

A deep Q-network (DQN) is a type of deep learning model that combines a deep CNN with Q-learning, a form of reinforcement learning. Unlike earlier reinforcement learning agents, DQNs can learn directly from high-dimensional sensory inputs.

Preliminary results were presented in 2014, with an accompanying paper in February 2015.[108] The research described an application to Atari 2600 gaming. Other deep reinforcement learning models preceded it.[109]

Deep belief networks

Convolutional deep belief networks (CDBN) have structure very similar to convolutional neural networks and are trained similarly to deep belief networks. Therefore, they exploit the 2D structure of images, like CNNs do, and make use of pre-training like deep belief networks. They provide a generic structure that can be used in many image and signal processing tasks. Benchmark results on standard image datasets like CIFAR[110] have been obtained using CDBNs.[111]

Notable libraries

- Caffe: A library for convolutional neural networks. Created by the Berkeley Vision and Learning Center (BVLC). It supports both CPU and GPU. Developed in C++, and has Python and MATLAB wrappers.
- Deeplearning4j: Deep learning in Java and Scala on multi-GPU-enabled Spark. A general-purpose deep learning library for the JVM production stack running on a C++ scientific computing engine. Allows the creation of custom layers. Integrates with Hadoop and Kafka.
- Dlib: A toolkit for making real world machine learning and data analysis applications in C++.
- Microsoft Cognitive Toolkit: A deep learning toolkit written by Microsoft with several unique features enhancing scalability over multiple nodes. It supports full-fledged interfaces for training in C++ and Python and with additional support for model inference in C# and Java.
- TensorFlow: Apache 2.0-licensed Theano-like library with support for CPU, GPU, Google's proprietary tensor processing unit (TPU),[112] and mobile devices.
- Theano: The reference deep-learning library for Python with an API largely compatible with the popular NumPy library. Allows user to write symbolic mathematical expressions, then automatically generates their derivatives, saving the user from having to code gradients or backpropagation. These symbolic expressions are automatically compiled to CUDA code for a fast, on-the-GPU implementation.
- Torch: A scientific computing framework with wide support for machine learning algorithms, written in C and Lua. The main author is Ronan Collobert, and it is now used at Facebook AI Research and Twitter.

Notable APIs

- Keras: A high level API written in Python for TensorFlow and Theano convolutional neural networks.[113]

Notes

1 ^ When applied to other types of data than image data, such as sound data, "spatial position" may variously correspond to different points in the time domain, frequency domain or other mathematical spaces.

2 ^ hence the name "convolutional layer"

3 ^ So-called categorical data.

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External links[edit]

- CS231n: Convolutional Neural Networks for Visual Recognition — Andrej Karpathy's Stanford computer science course on CNNs in computer vision
- An Intuitive Explanation of Convolutional Neural Networks — A beginner level introduction to what Convolutional Neural Networks are and how they work